



# LAMBDA @ HSE CS

Laboratory for Methods for Big Data Analysis

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YSDA

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# Quick self-intro



Head of LHCb Yandex School of Data Analysis (YSDA) team  
Head of Laboratory ([link](#)) of methods for Big Data Analysis at Higher School of Economics (HSE),

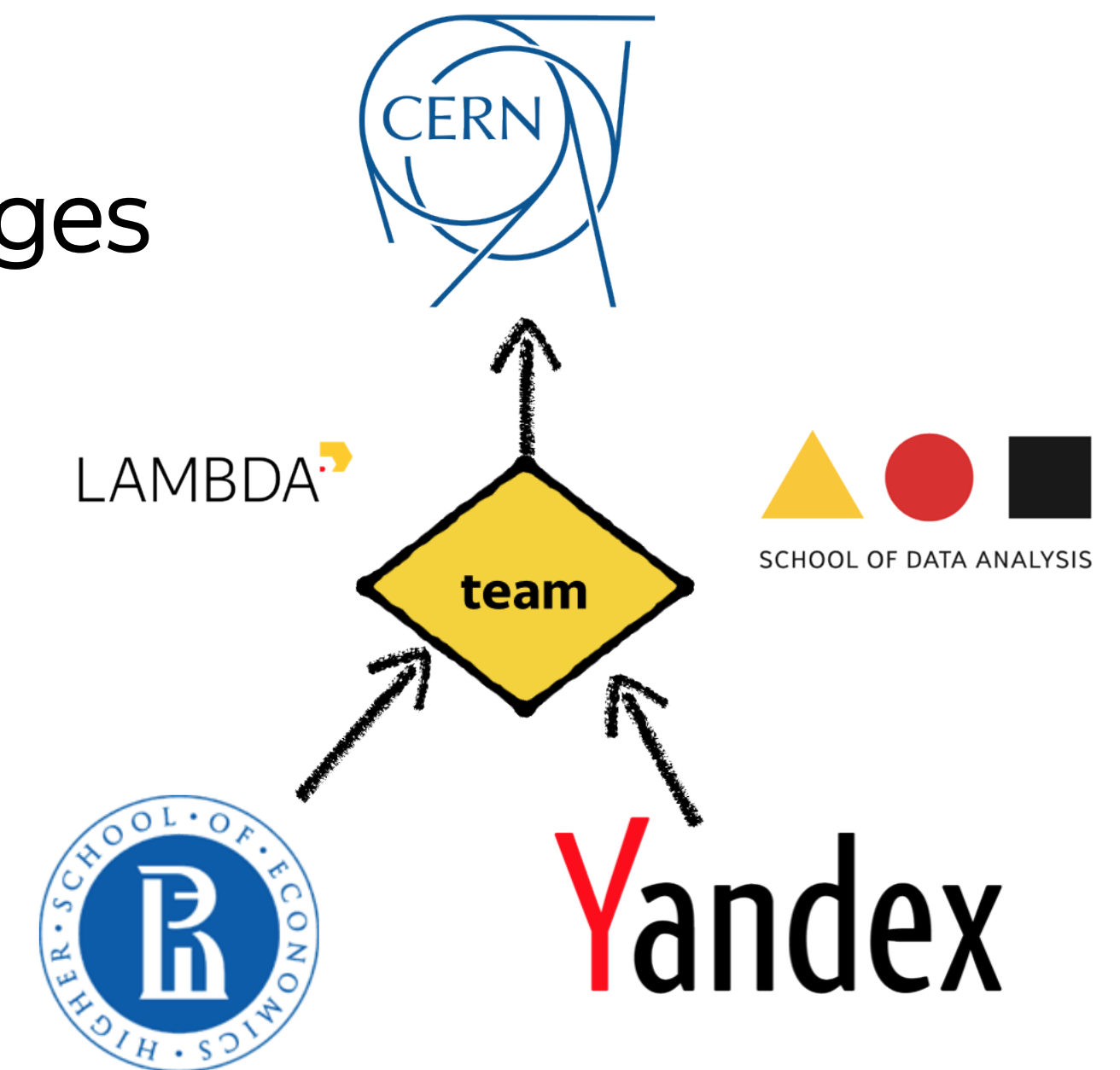
- › Applications of Machine Learning to natural science challenges
- › HSE has joined LHCb in 2018!

Co-organizer of Flavours of Physics @Kaggle (2015)

Co-organizer of TrackML challenge (2018)

Education activities (ML at ICL, ClermonFerrand, URL Barcelona, Coursera)

- › Summer school on Machine Learning in Hamburg, 2019, Oxford 2018, Reading 2017, Lund 2016, ...



# Main Laboratory Focus

Development of Machine Learning methods for solving tough fundamental science challenges;

Collaboration with leading international research institutions and industry for solving advanced applied problems;

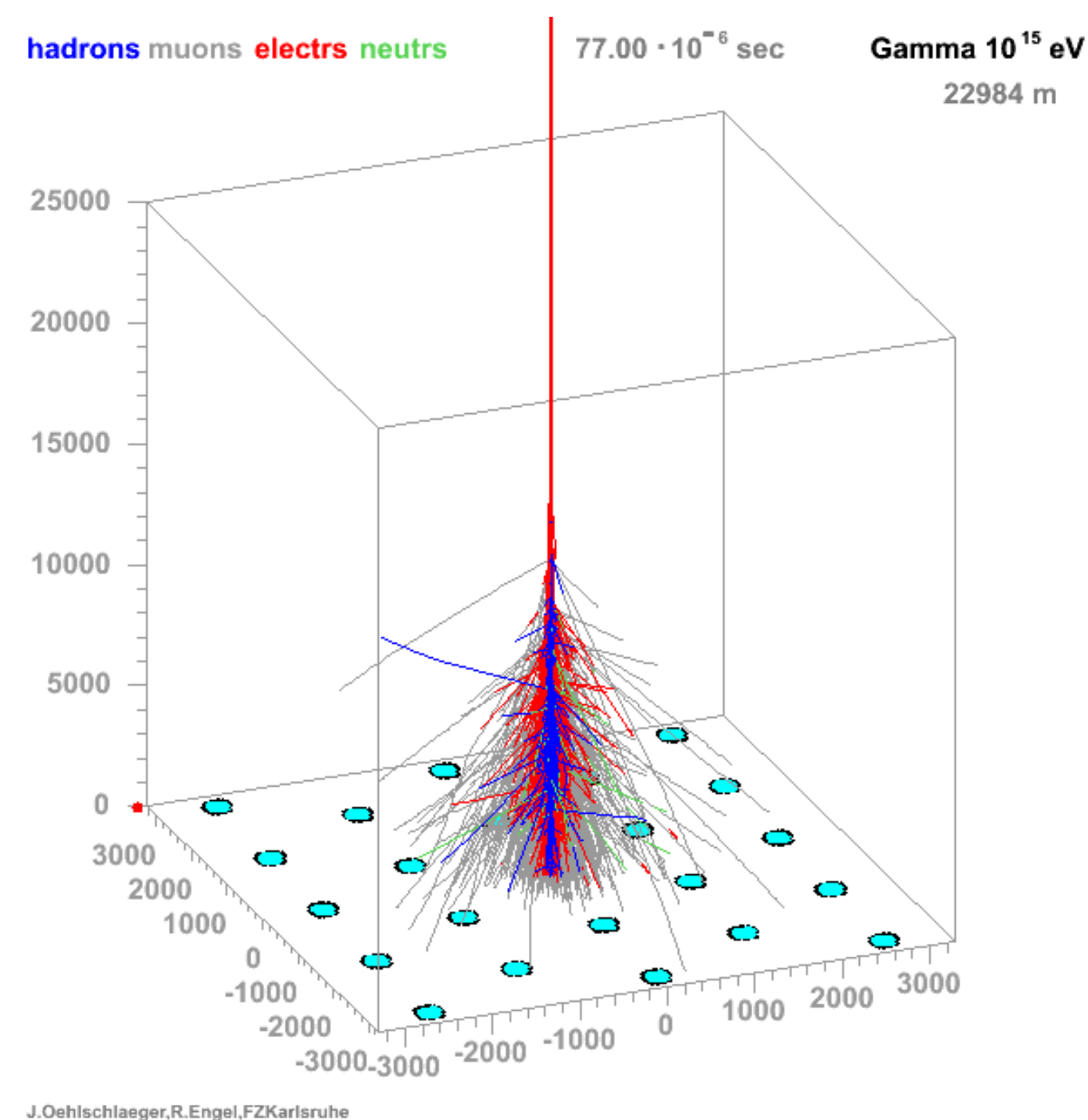
Promoting Machine Learning in Natural Science communities.



# Scientific Research Highlights



# CRAYFIS muon trigger for



Up to  
**98%**  
speedup for running deep  
neural net model

## Task

CRAYFIS experiment proposes usage of private mobile phones for observing Ultra-High Energy Cosmic Rays. Distributed observatory, seeking for particles of energies  $> 10^{18}$  eV. Design trigger for mobile device that can catch

- › an intensive air shower from UHECR (occurs in less than microseconds);
- › supports high frame rate (10 Hz)
- › trigger on minimally ionizing particles (assuming that such particles leave traces with brightness comparable to the level of intrinsic camera noise).

## Data used

- › CRAYFIS Simulated sample

## ML Metrics

Linear combination of

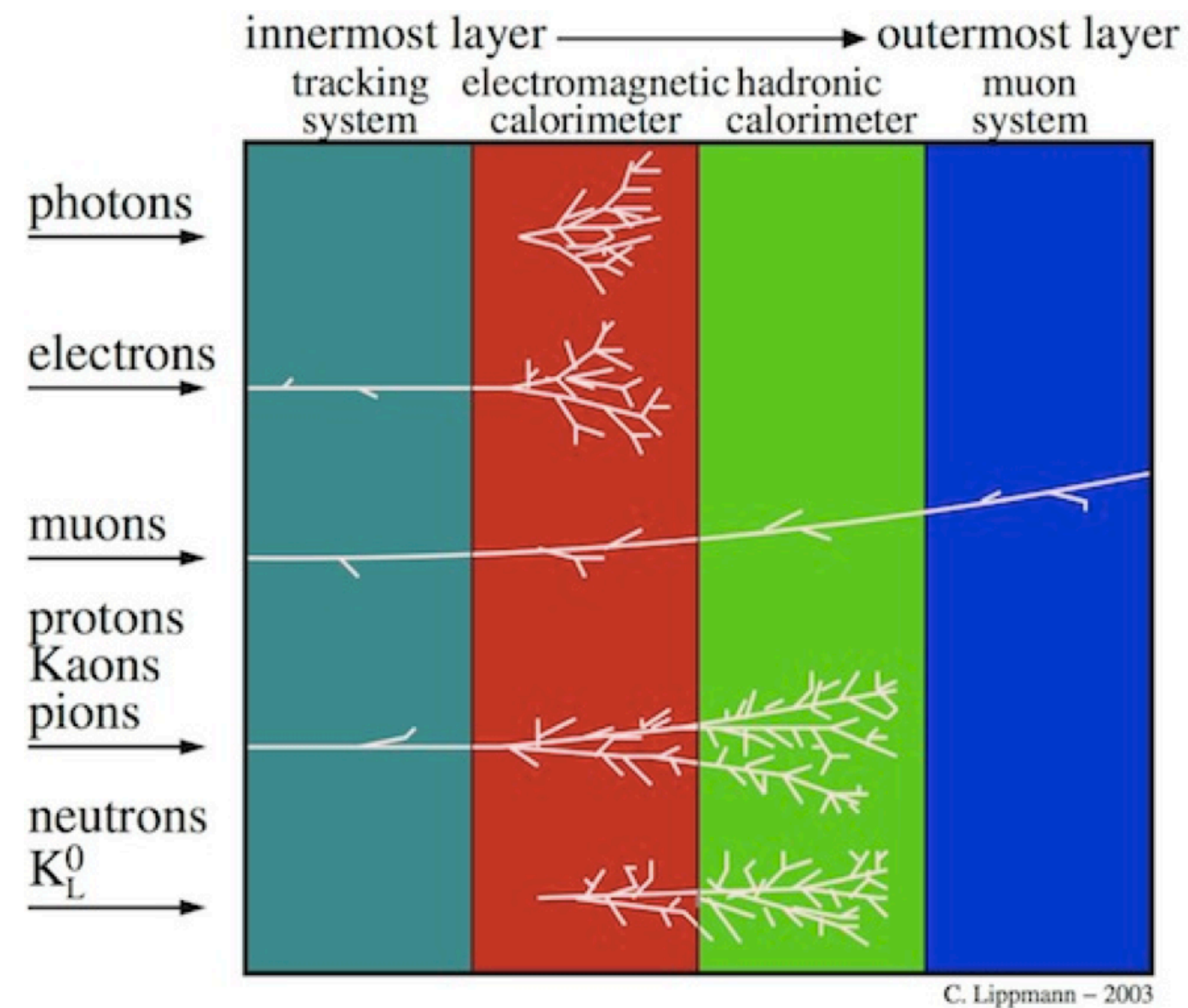
- › weighted cross-entropy;
- › computational complexity.

## Result

- › for just 1.4 times more computational cost than simple cut, gives signal efficiency of 90% and background rejection 60%;
- › computational complexity is 0.02 of regular convolutional network;
- › <http://bit.ly/2nb7gfx>

# LHCb particle identification

Case



Up to  
**50%**  
algorithm error reduction

## Task

identify charged particle associated with a track (multiclass classification problem);

particle types: Electron, Muon, Pion, Kaon, Proton and "Ghost";

combine information from LHCb subdetectors: CALO, RICH, Muon and Tracker;

## Data used

- › LHCb Simulated sample

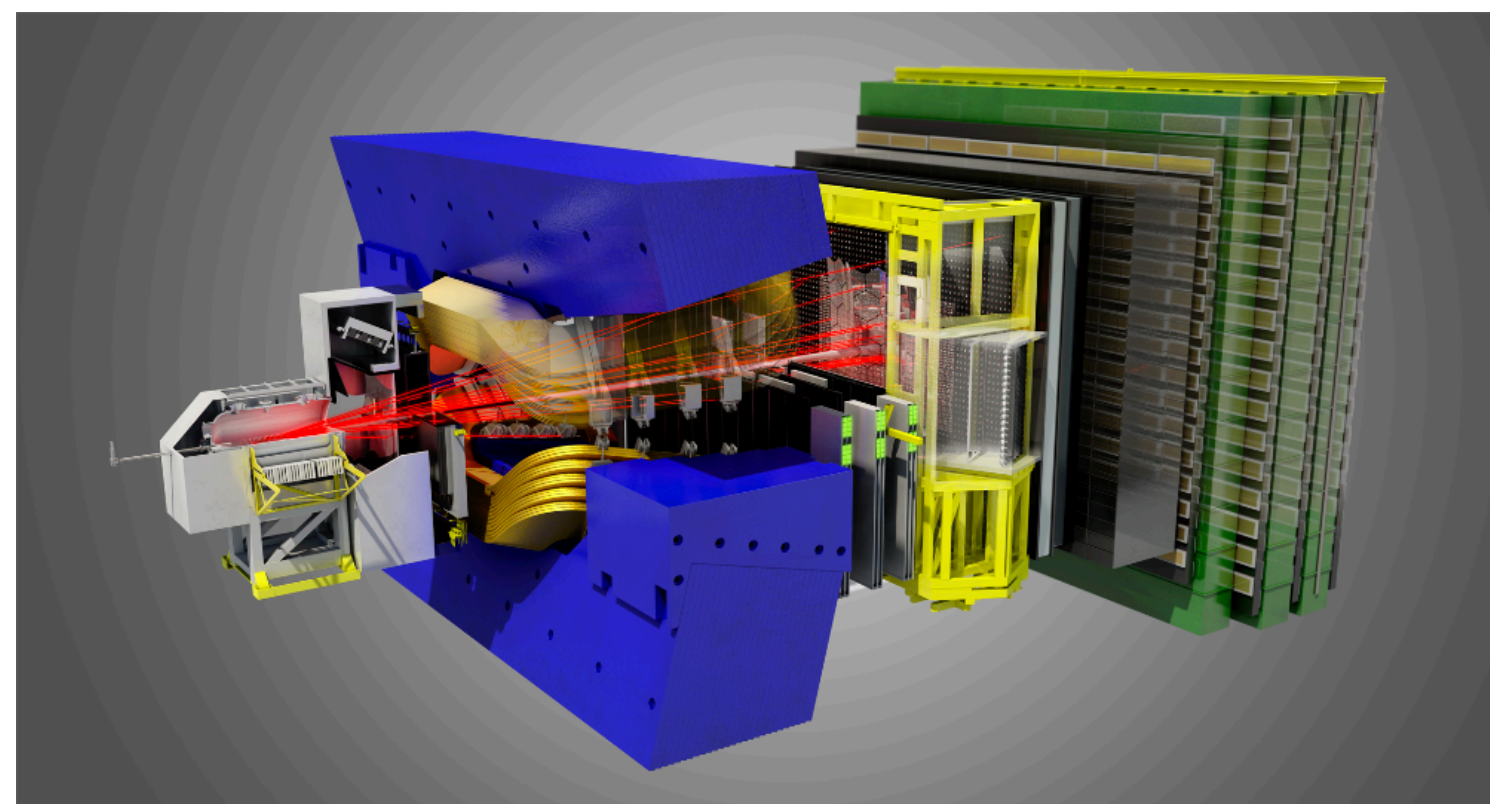
## ML Metrics

- › ROC AUC one vs all,
- › model flatness

## Result

- › Blended NN model that has error rate half less than baseline for some of the particles;
- › Blended BDT model with same ROC AUC, but that is flat wrt given features;
- › <http://bit.ly/2l0yvXc>

# LHCb particle ID generation



## Task

generate particle identification probability for simulated samples

particle types: Electron, Muon, Pion, Kaon, Proton and “Ghost”

based on information from LHCb subdetectors

## Data used

› LHCb real calibration samples

## ML Metrics

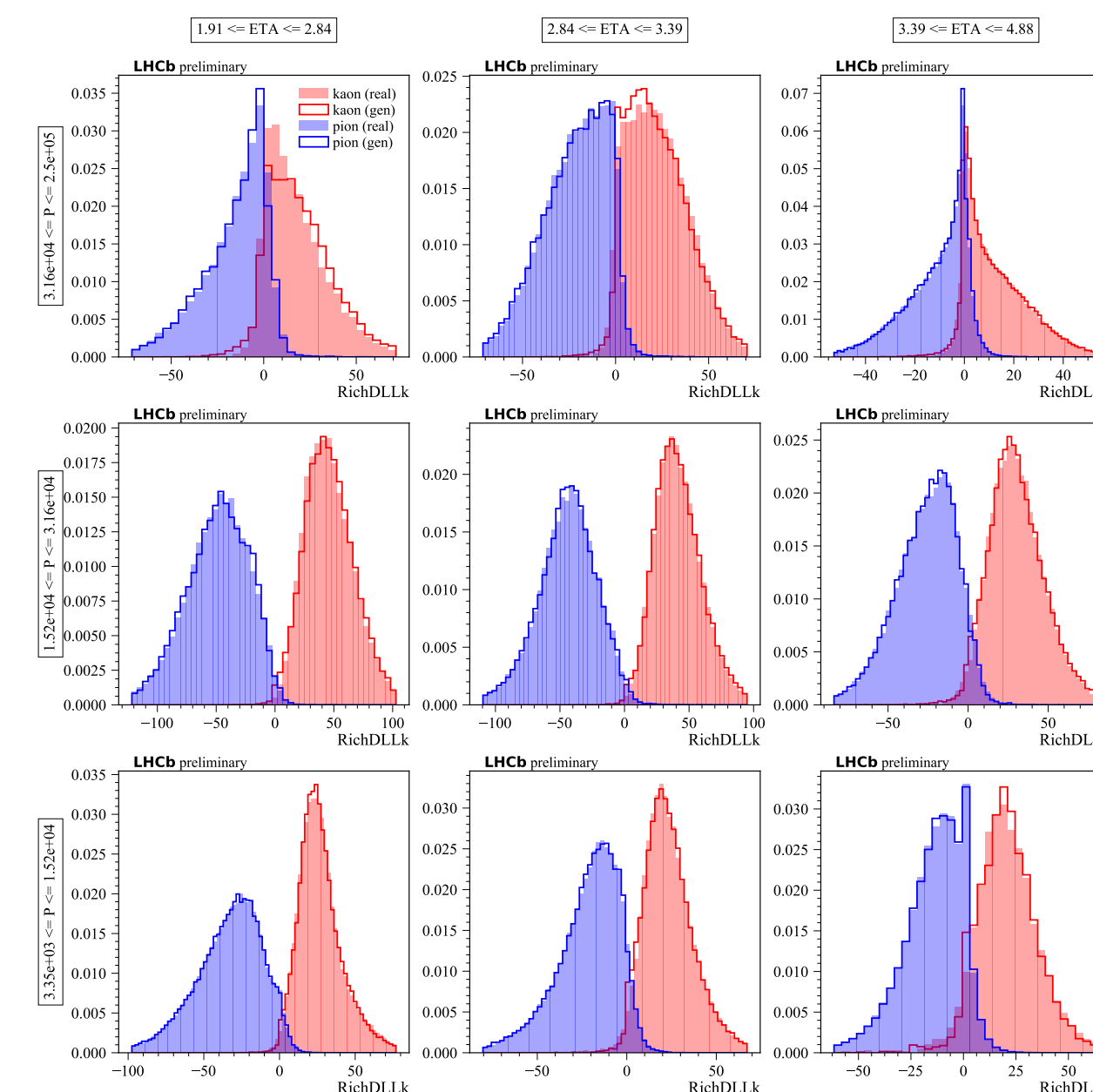
› AUC similarity

## Result

› NeuralNet-based simulator is 100 times faster than the full simulation

› being trained on real data, emulator is more precise than the one based on full simulation

› <https://doi.org/10.1016/j.nima.2019.01.031>



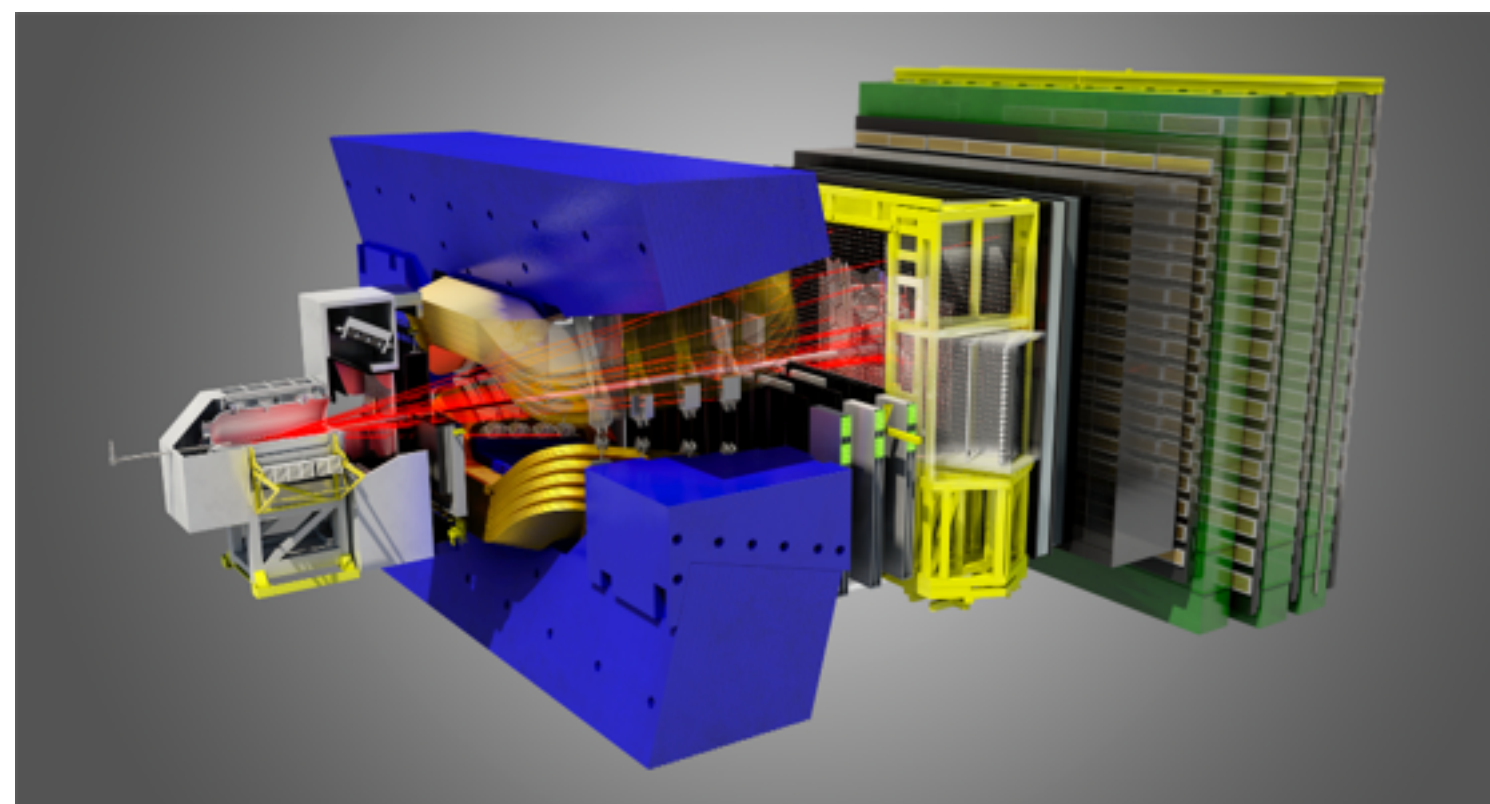
Neural Net-based generator simulator is

**100x**

faster than the full simulation

# LHCb fast simulation of detector response

Case



## Task

generate stochastic response in the calorimeter of the detector

particle types: Electron, Photon, Pion, Kaon, Proton

## Data used

› LHCb simulated samples

## ML Metrics

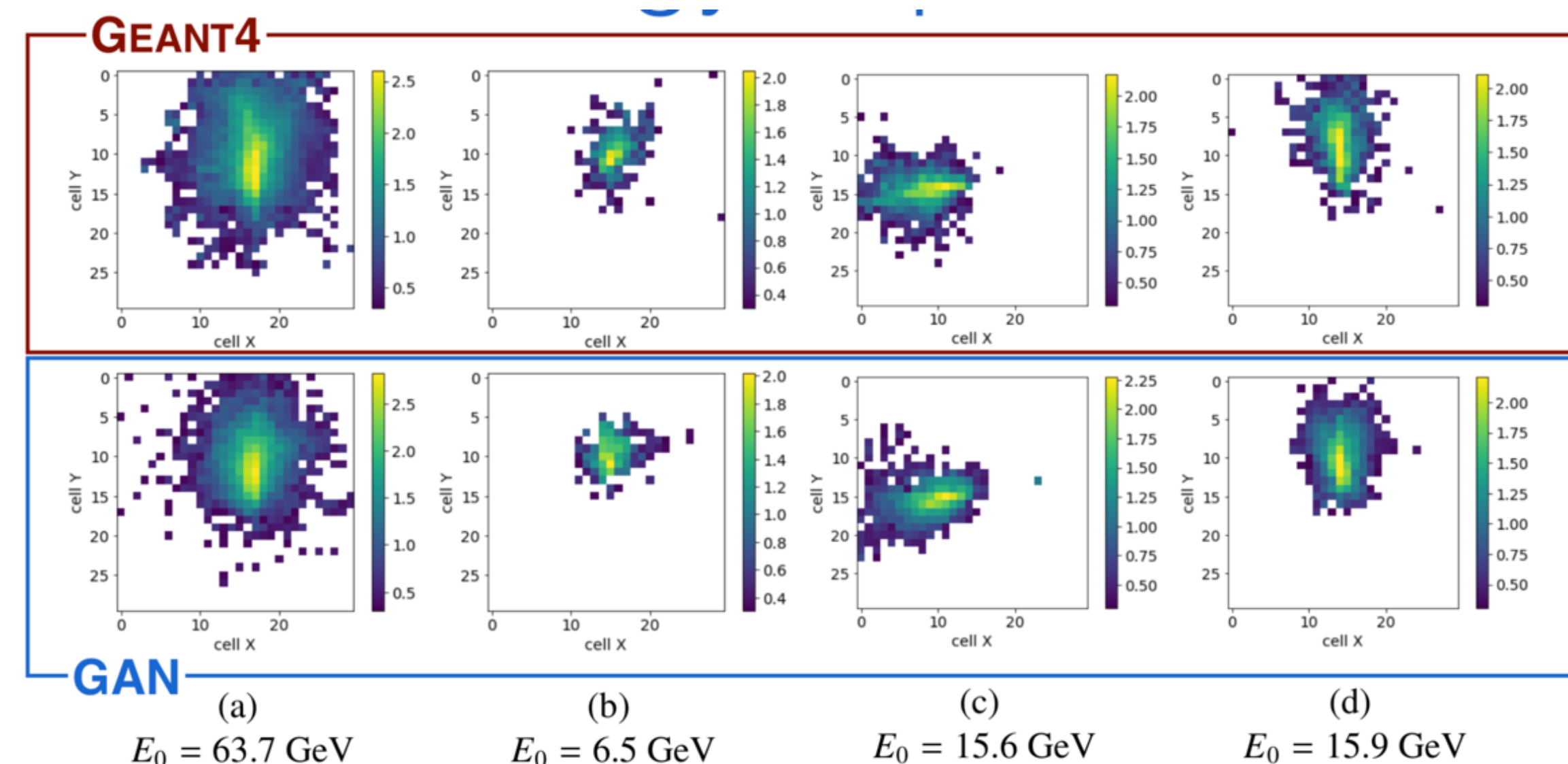
› physics properties of generated clusters

## Result

› NeuralNet-based simulator is 1000 times faster than the full simulation

› <https://doi.org/10.1051/epjconf/201921402034>

**1000x**  
speed-up

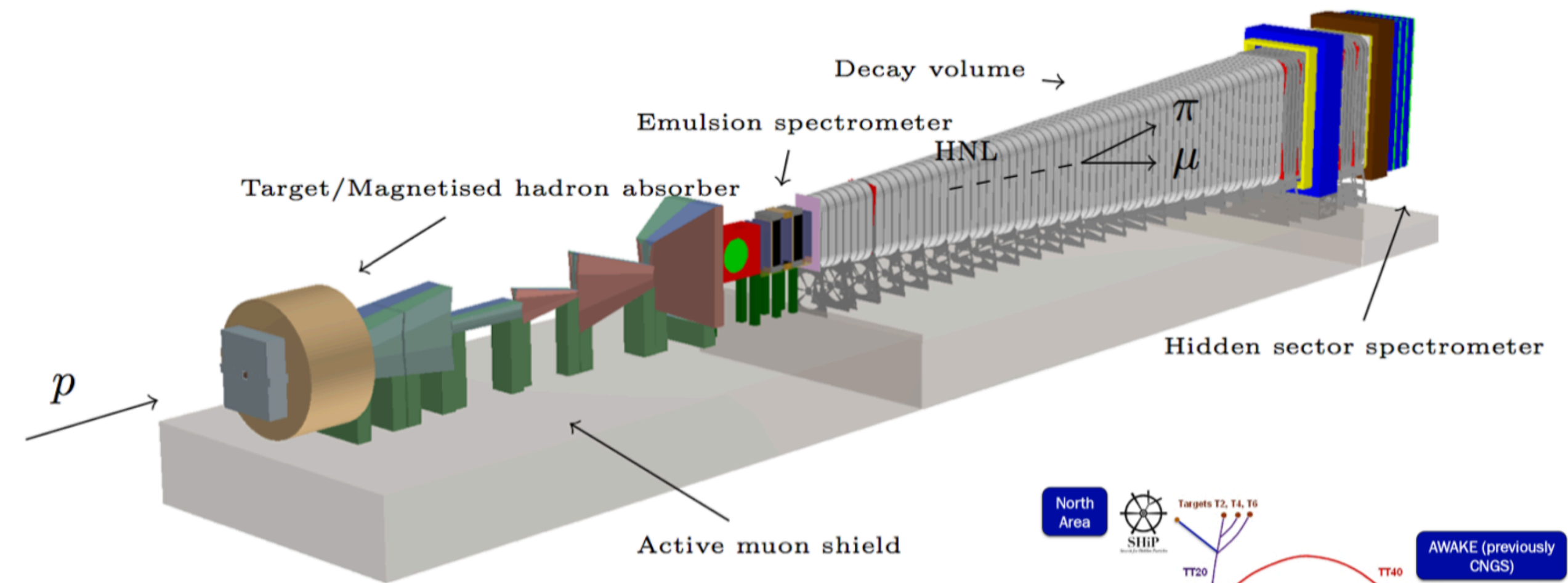




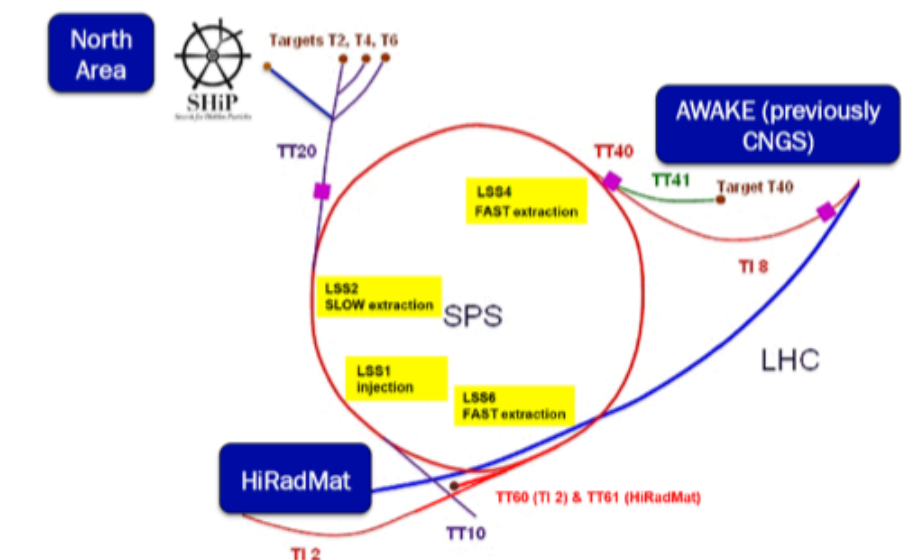
# SHiP shield optimization

**Problem:** find complex shape of muon deflection component. 50-dimensional space.

**Solution:** with the help of non-gradient optimization and advanced simulation technique we have discovered configuration that is 25% lighter (saves CHF 1M) and has the same physics properties.



◇ Search for Hidden Particles



<http://iopscience.iop.org/article/10.1088/1742-6596/934/1/012050/meta>

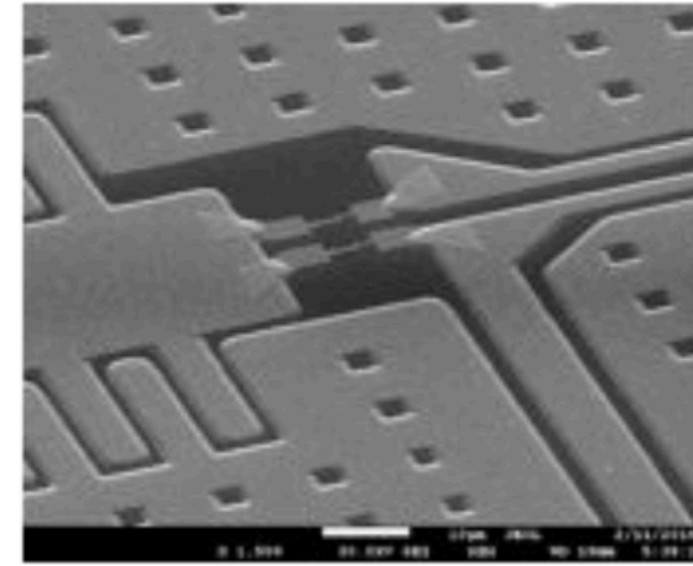
# Quantum system control

**Problem:** learn to control qbit to switch from one state to another

**Solution:** with the help of Reinforcement Learning and differentiable simulator the accuracy and speed of convergence has increased dramatically.

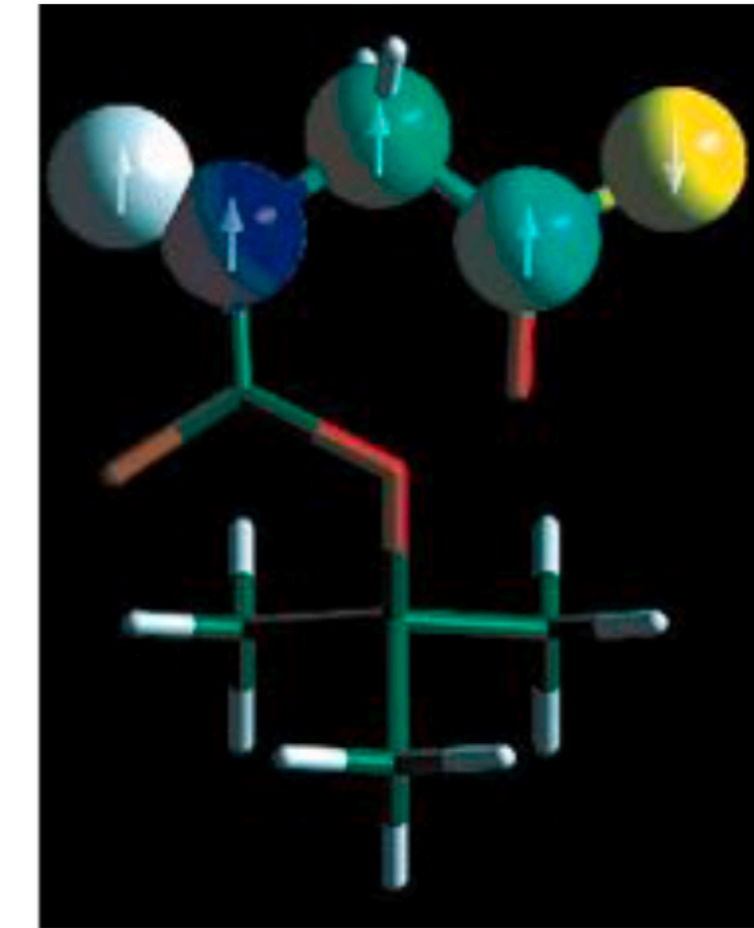
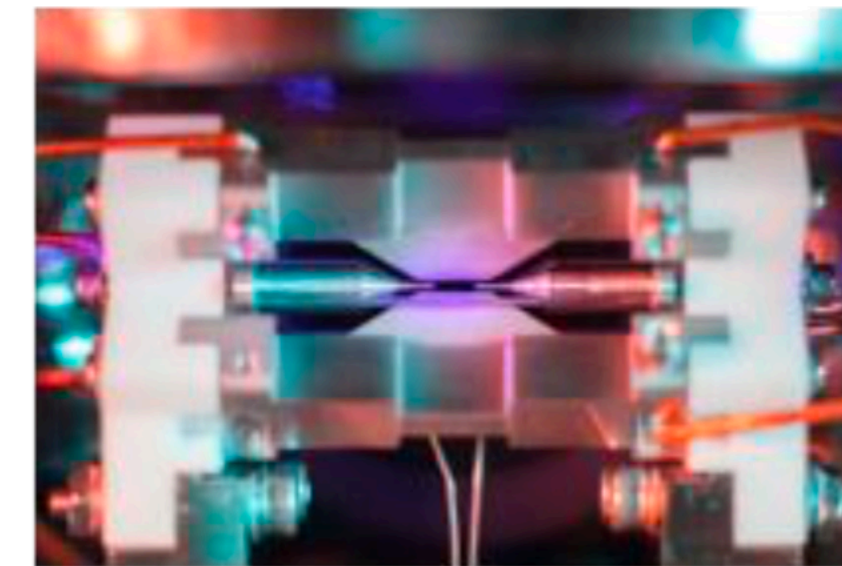
**Status:** waiting for experimental confirmation of those results

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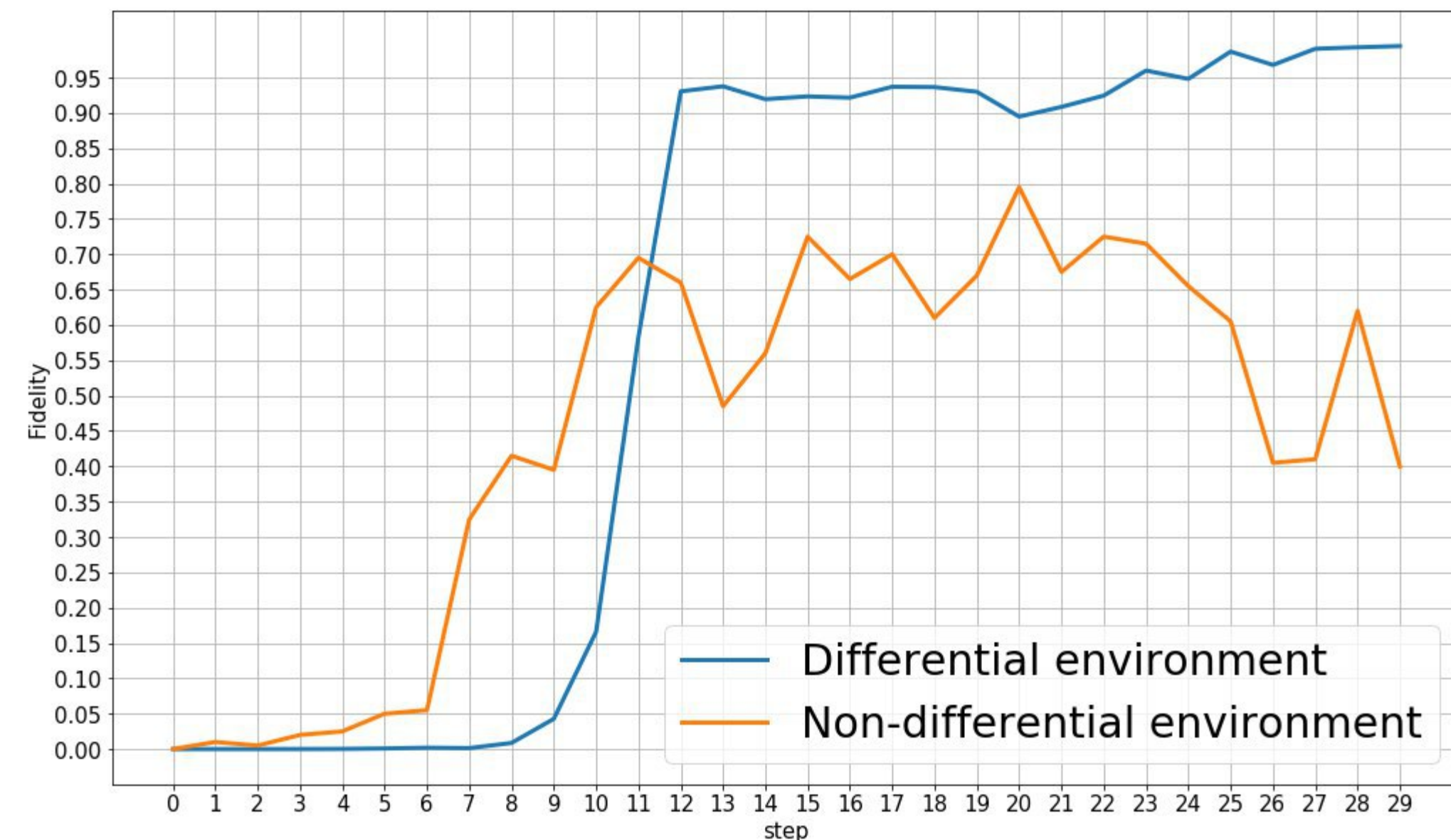


Superconducting quantum circuit

Atomic traps



NMR



# “Industrial” Research Highlights



# Data storage optimisation



## Challenge

The Large Hadron Collider detectors take captures of every notable particle interaction, which piles up to over 5 PB of data a year. But the market price for 1 PB of data storage per year runs as high as 1 million dollars.

# \$4m

**maximum yearly projected savings on data storage**

## Task

To cut storage costs and to determine which files should be stored on which kind of medium, to improve the effectiveness of data access

## Data used

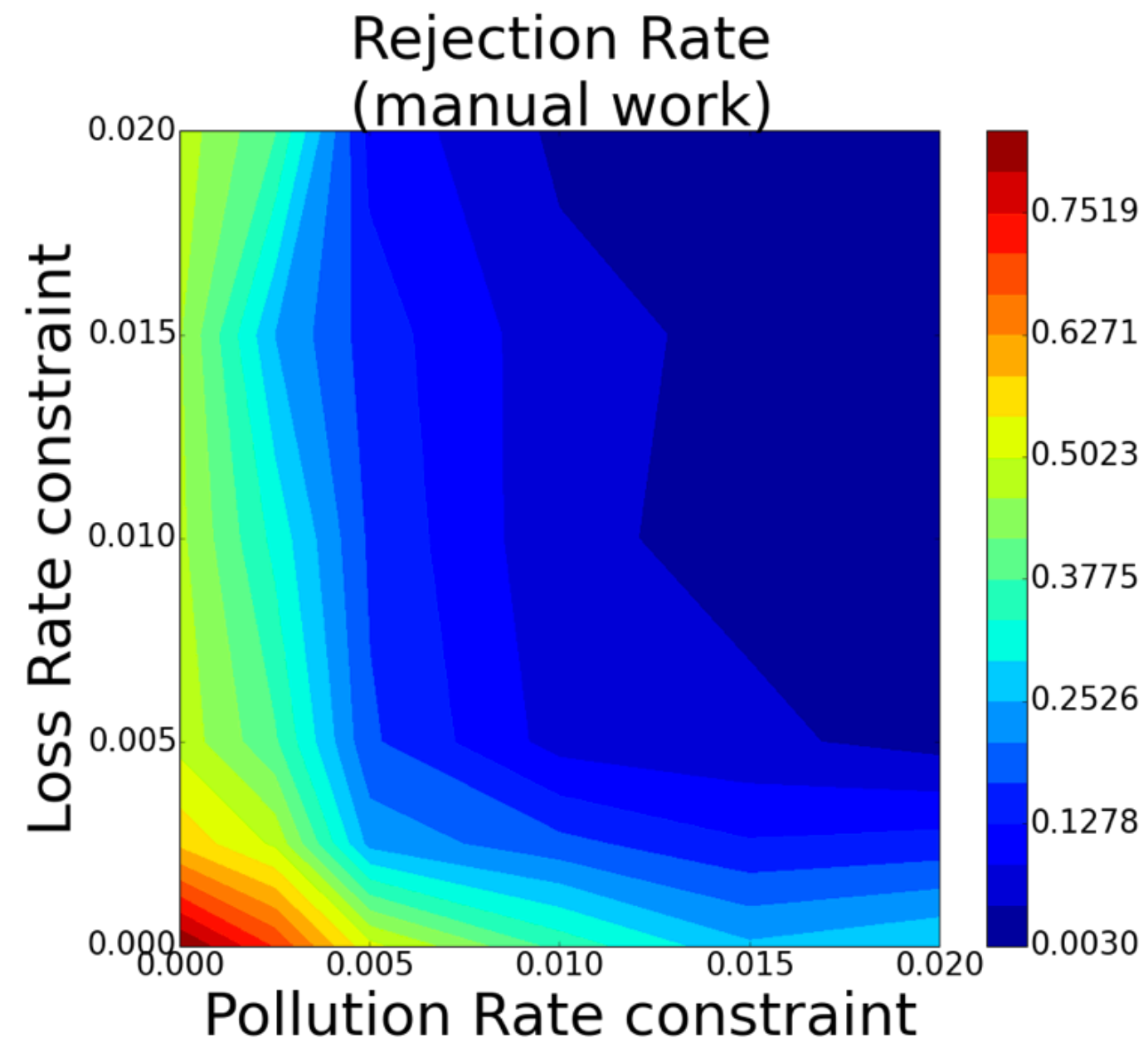
- › Historical data on the access history of every file generated by LHCb and the collision simulators (each file catalogued by several features, like file size, number of existing file copies, access frequency, longest duration for which the files hadn't been accessed, file origin, etc.)

## Result

- › Data storage optimisation by 40%
- › A model that allows saving up to 4 petabytes (more than 4 million gigabytes) of storage a year – the standard rate for storage is \$4m, annually
- › The model has been deployed at the beginning of the Collider's Run-II in the Summer of 2015

# CMS data certification / anomaly detection

Case



## 80%

saving on manual work on data certification tasks

## Task

Traditionally, quality of the data at CMS experiment is determined manually. It requires considerable amount of human efforts;

## Data used

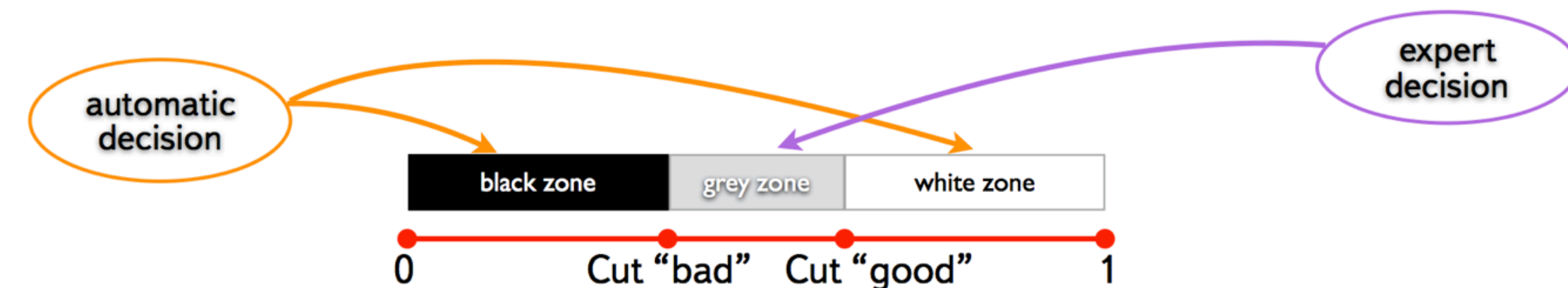
- › CERN open data portal 2010;
- › Features: Particle flow jets, Calorimeter Jets, Photons, Muons;
- › The dataset was labeled by CMS experts (~3 FTEs).

## ML Metrics

- › ROC AUC, precision

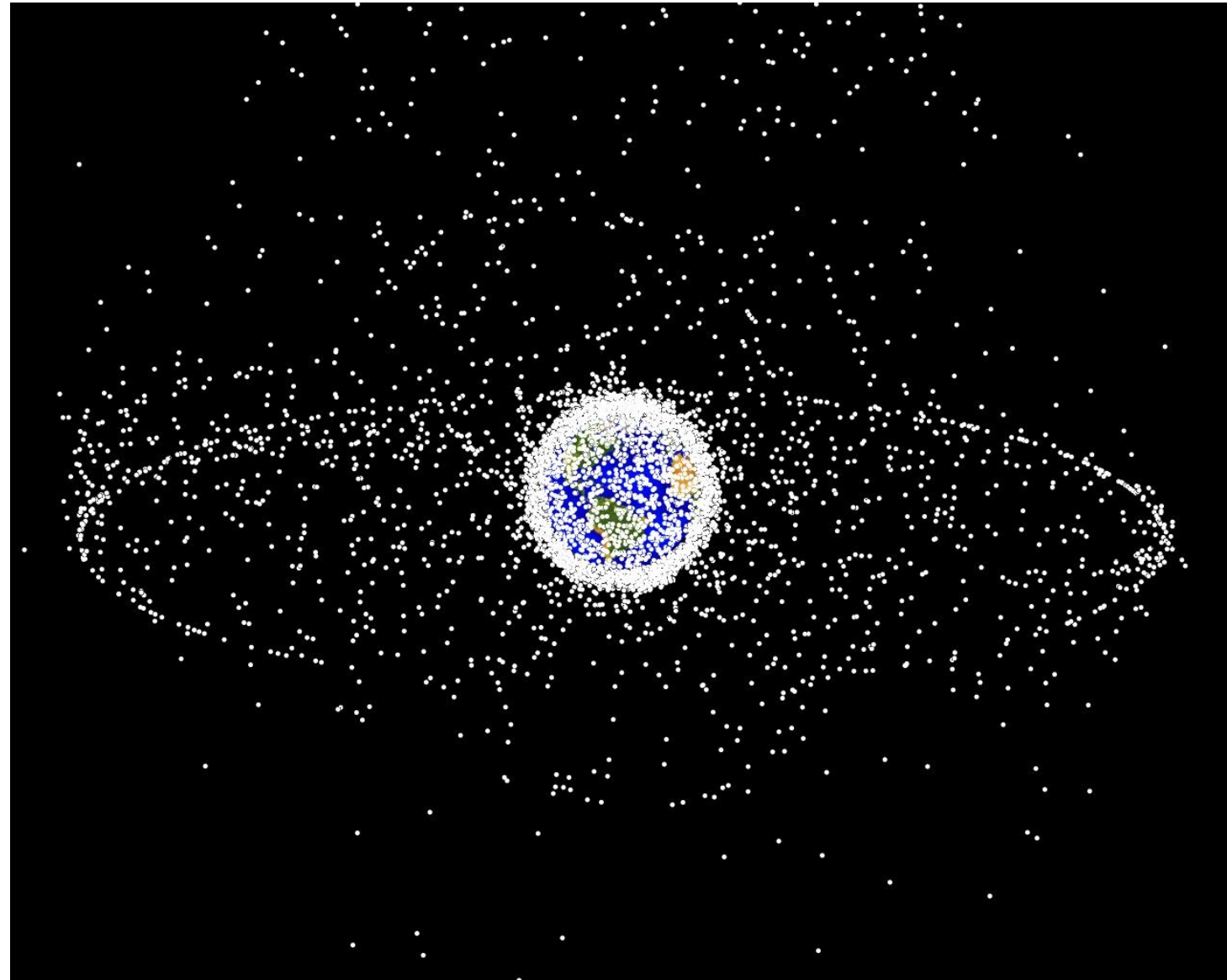
## Result

- › ~80% saving on manual work is feasible for Pollution & Loss rate of 0.5%.
- › Next steps: adopt technique for 2016 data & run in production
- › <http://bit.ly/2I0MLiN>



# Satellite Control : Collision Avoidance

Case



[https://en.wikipedia.org/wiki/Space\\_debris](https://en.wikipedia.org/wiki/Space_debris)

## 2·10<sup>-4</sup> %

probability of collision for 99% cases

## Task

Reaction to a collision threat must be automated for large constellations (e. g. 10k planned in Starlink)

Decision is not a simple optimisation problem, it must consider many constraints

## Methods

reinforced learning

## Test

- › 100 simulated conjunctions on Low Earth Orbit

## Result

- › In the majority (68%) of cases SpaceNav fulfils all the constraints
- › In almost every case (99%) it reduces the total collision probability to  $2 \cdot 10^{-4}$
- › The algorithm was configured to save fuel, by relaxing this requirement, any risk level can be achieved

[arXiv:1902.02095](https://arxiv.org/abs/1902.02095)

# Satellite Control : Collision Avoidance

Case



[https://en.wikipedia.org/wiki/Space\\_debris](https://en.wikipedia.org/wiki/Space_debris)

# 99 %

failure detection rate, while  
false alarm rate is as low as 5%

## Task

Anomalies and failures detection algorithm for early recover of the system

Construction of Digital Twin of Storage System for generation of rare events

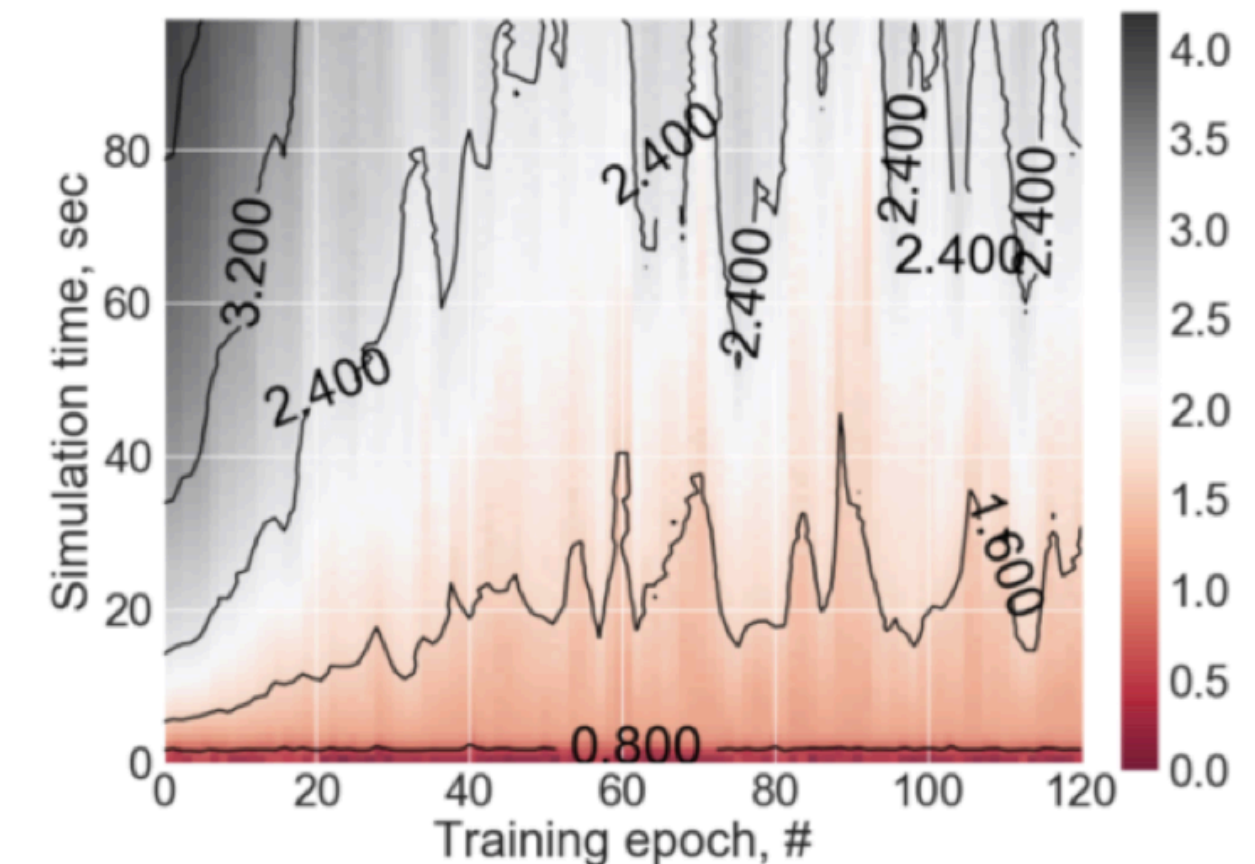
## Methods

Proposed algorithm for anomaly detections for timeseries and implemented it in production-ready library: “Nostradamus”

Proposed combination of event-driven simulator and reinforcement learning control for simulator fine-tuning: “DeepController”

## Result

- › Failure Detection Rate is up to 99% while keeping False Alarm Rate at 5%
- › After ~100 epochs quality of simulation improves in several times on target metrics in comparison with simulator without RL-control

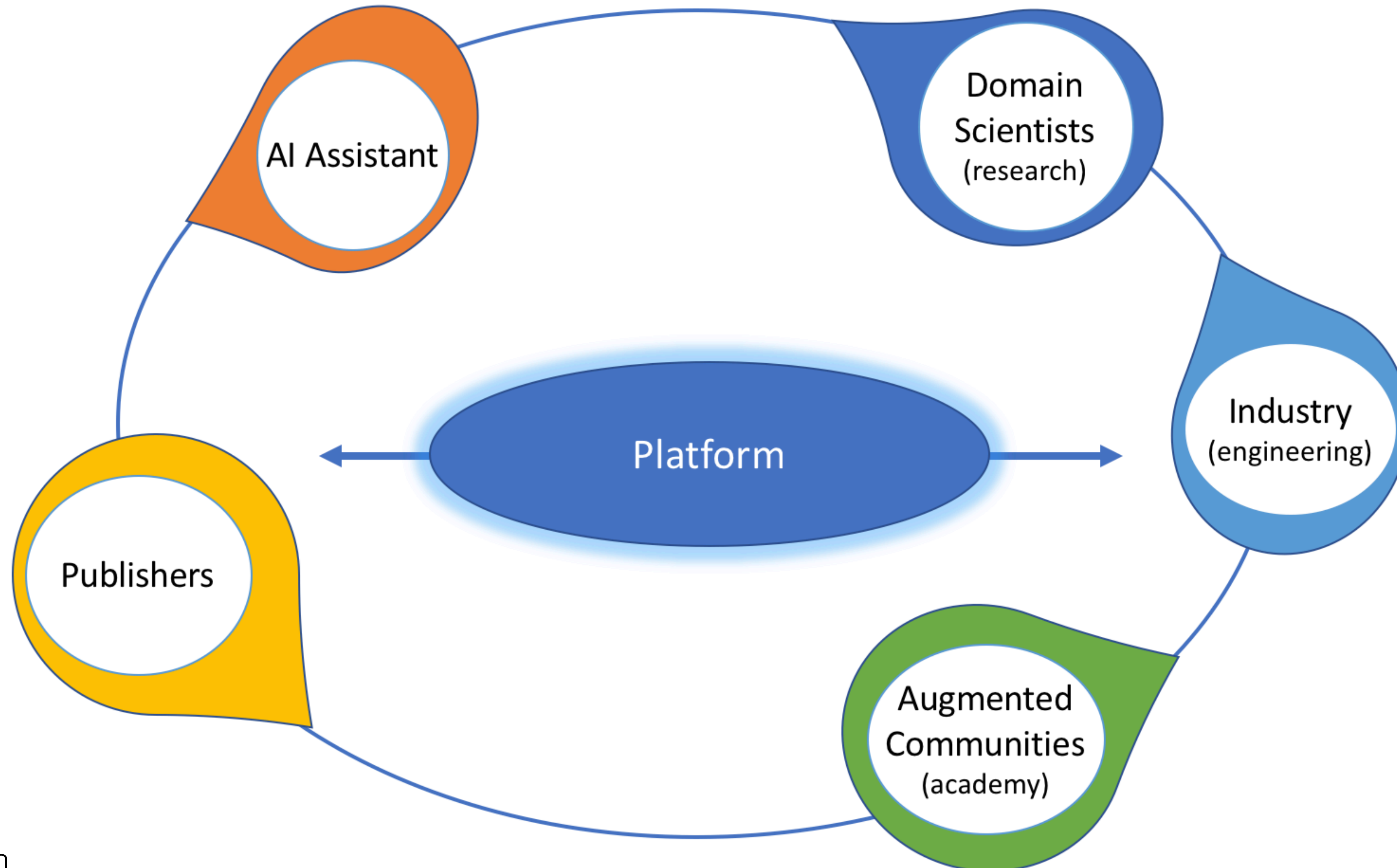


# Co-research methodology

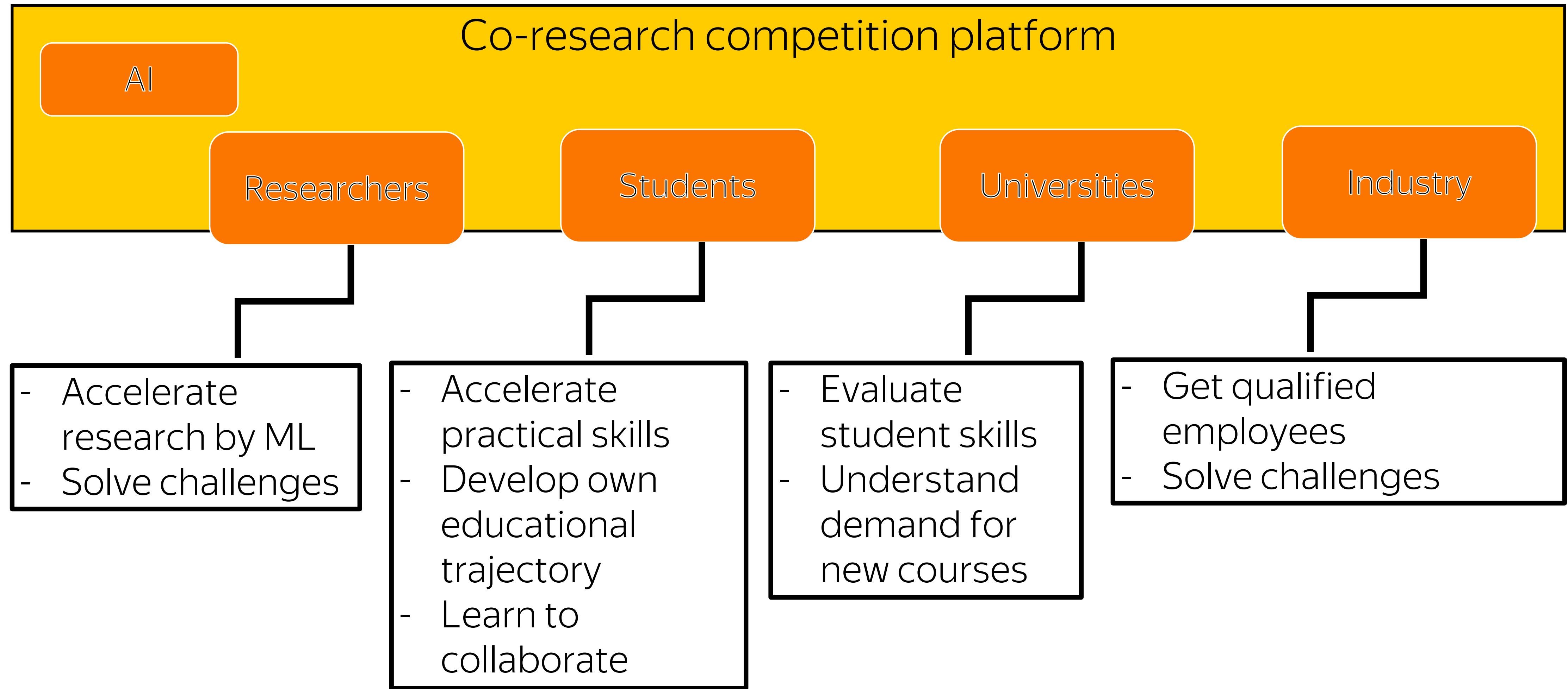




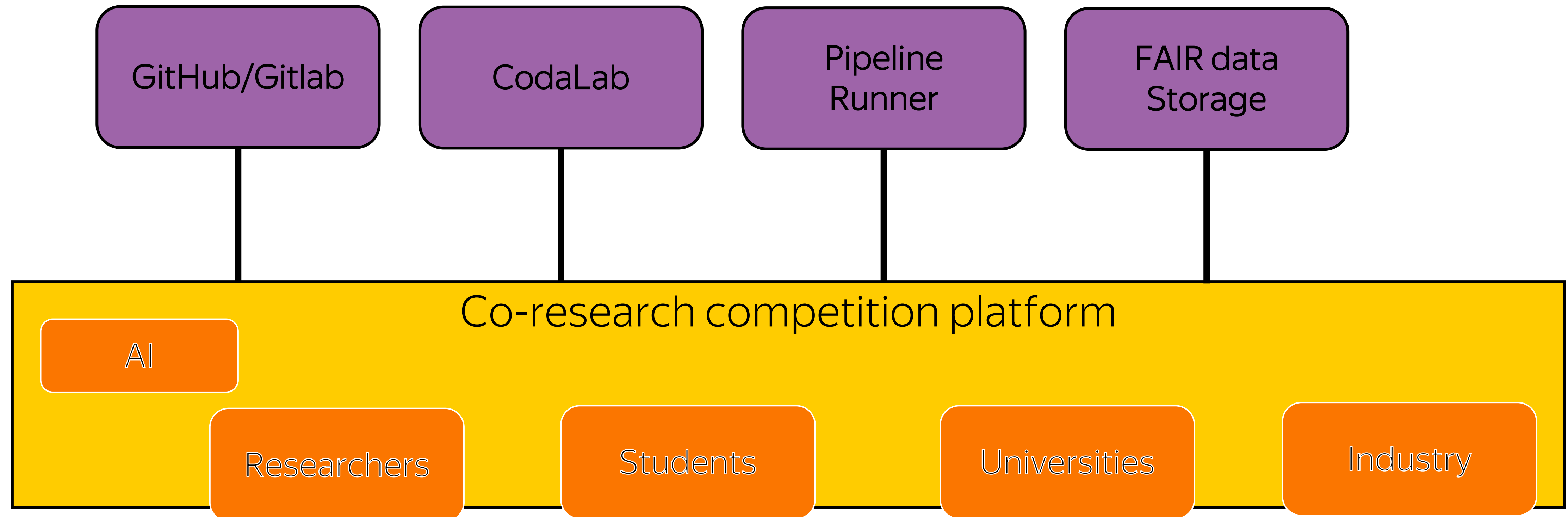
# Co-research platform



# Co-Research Platform overview



# Co-Research Platform overview



<https://coopetition.coresearch.club>

# Our collaborators

## Particle physics

- › LHCb (CERN), SHiP (CERN), CMS (CERN), OPERA (INFN), NewsDM (INFN)

## Astrophysics

- › <http://www.sai.msu.ru/>

- › Institut für Astronomie und Astrophysik Tübingen

Neuroinformatics, Institute of Cognitive Neuroscience

Space industry, Roscosmos

Metal production industry, MMK

# Summary

LambdaLab is focused on adopting advanced ML methods to challenging problems in Natural Science and Industry

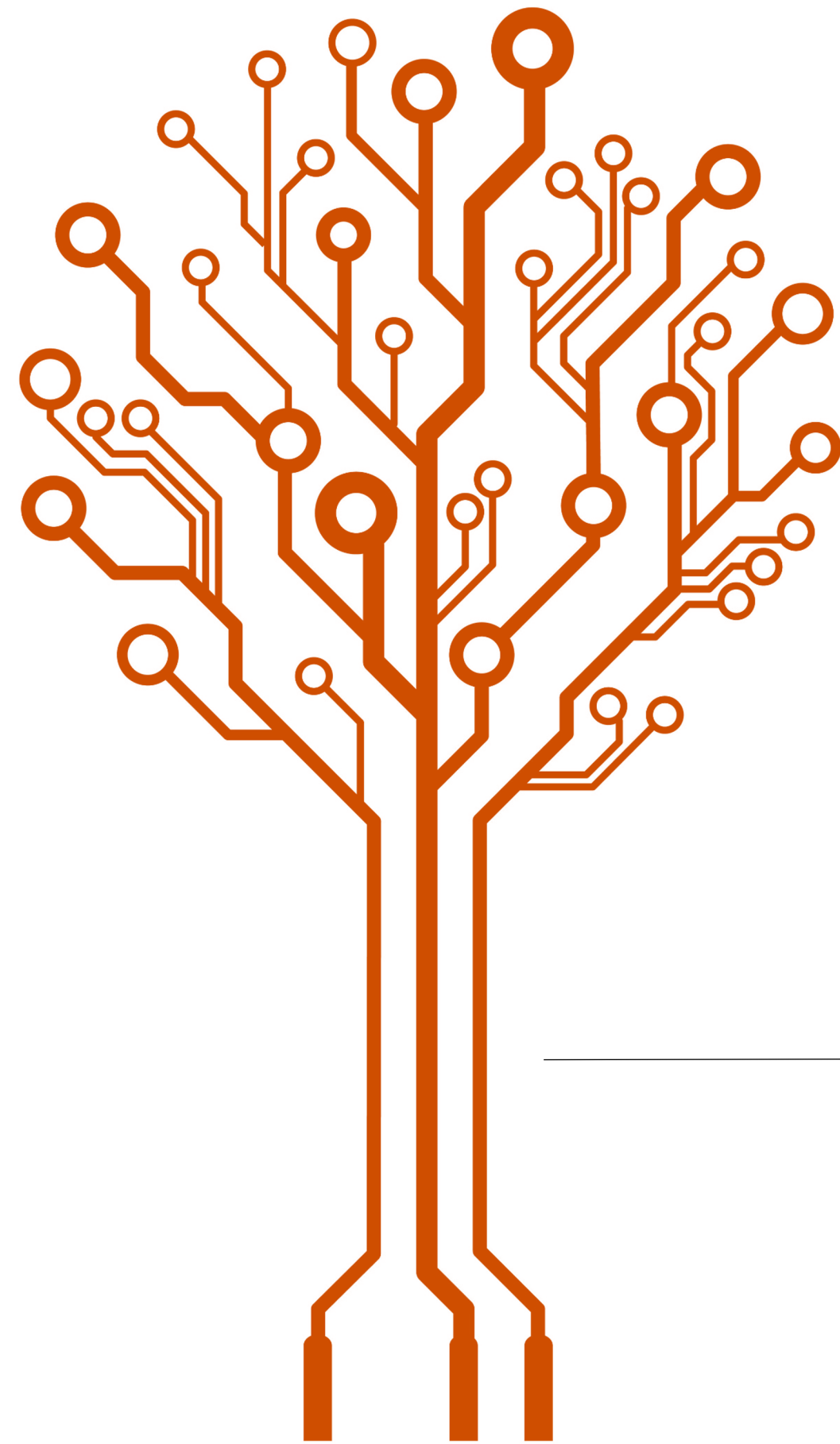
Many more completed and ongoing projects are not included in this presentation

Educational efforts include regular lectures, courses, schools  
Staffed by 3 senior scientists, 6 researchers, 10 PhD students, MS students, ...

Close cooperation with teams in France, Germany, Italy, Switzerland, UK

30+ publications on applied ML for last 3 years

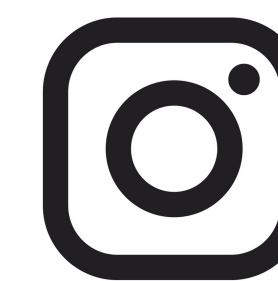
# Thank you



## Innovate with LAMBDA!

2020	
Head count	35
Applied Projects	9
Research Projects	30+

2015	
Head count	12
Applied Projects	2
Research Projects	10



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# Backup



# Recent research highlights

Advanced anomaly detection methods

Models capable of training on mixture of real and simulated data

Advanced generative models, digital twins

Differentiable surrogate models